# Brain freeze: outdoor cold and indoor cognitive performance

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# Brain Freeze: Outdoor Cold and Indoor Cognitive Performance

**Abstract**

We present first evidence that outdoor cold temperatures negatively impact indoor cognitive performance. We use a within-subject design and a large-scale dataset of adults in an incentivized setting. The performance decrement is large despite the subjects working in a fully climate-controlled environment. Using secondary data, we find evidence of partial adaptation at the organizational, individual and biological levels. The results are interpreted in the context of climate models that observe and predict an increase in the frequency of very cold days in some locations (*e.g.* Chicago) and a decrease in others (*e.g.* Beijing).

*Keywords:* Climate change, Cold temperature, Cognitive productivity, Climate resilience, Adaptation

## 1. Introduction

How is the cognitive performance ("mental productivity") of people working indoors, in climate-protected environments, impacted by outdoor cold? To what extent can adaptation at the organizational, personal, or biological level insulate against any decrement in performance?

This paper provides what we believe to be first evidence that outdoor cold has a detrimental impact on performance, and to speak in detail to issues of adaptation. Data comes from a large sample of subjects in a fully-incentivized setting.

Understanding the link from exterior temperature to indoor work is a key step in any projection of how changing climate might impact productivity in sectors that are not as obviously climate-exposed as, for example, agriculture and tourism. While the attention of climate research in economics has been on increasing average temperatures and the effects of hot days on human outcomes, there is a dearth of evidence of any impacts of cold. This is an important gap in knowledge because climate models predict changes in the frequency of cold weather.[2] Even as average

[1]This line reserved for identifiable author notes.

[2] Historically Chicago (with a mean December temperature of -3°C) has averaged 11 days in

temperatures increase, some places will experience more very cold days by the end of this century (e.g. Chicago), while other places will experience less (e.g. Beijing). The effect of cold on the human body and behavior is distinct from that of heat and works through different channels. Furthermore, there exists evidence that the mechanisms for adaptation are different.

The outcome data that we use for performance is 638,238 exams taken by 66,715 adult students over a 9 year period at the University of Ottawa, a large, comprehensive, research-intensive public university. It operates from a main campus located in the heart of the capital city. While the extent to which impacts on exam performance would also be seen in workplace productivity is an open question, academic scoring reflects a clean measure of mental proficiency which, at a minimum, seems likely to correlate with performance in a range of brain-intensive work tasks. At least three features of our setting make it an ideal context to explore our research question:

(1) It provides good quality cognitive performance data on a large number of working age adults in an incentivized setting under *cold* and *very cold* exterior conditions (average daily temperature in our sample ranges from -17°C at the 5th percentile to 5°C at the 95th). The data's panel structure means we observe the same subject's performance under alternative outdoor-temperature treatments (on average around ten per subject), allowing inference based on within-subject variation. This expels any time invariant within month unobserved characteristics of individuals that might influence performance.

(2) The nature and scheduling of the cognitive tasks faced by subjects are determined far in advance and are insensitive to subsequent temperature realizations. This allows us to rule out selection effects due to displacement-in-time of activity in response to conditions that could contaminate inference in other settings.

(3) While outdoor temperatures vary widely, we are able to provide direct evidence that the indoor temperature for subjects are held almost exactly constant by modern climate-control technology. As such, the most obvious technological protection against extreme temperature is fully-exploited, and any effects we identify account for that margin of adjustment.

Secondary data allows us to investigate non-organizational adaptation. While an

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December where temperature remained below freezing for the whole day and a further 16 days in a typical January. The number of cold days in that and other mid-latitude North American cities such as Detroit and Toronto, is projected to increase between now and end of century due to arctic warming and increasing instability in the polar vortex (Kolstad et al., 2010; Cohen et al., 2018). Beijing has a winter temperature profile similar to that of Chicago and is projected to get less cold days, particularly due to predicted changes in polar vortex states Kretschmer et al. (2018).

employer, for example, can heat the workplace, there are actions that individuals can take to protect against outdoor temperature conditions. We test whether reducing direct exposure through living close to place of work provides mitigation. To investigate the hypothesis that personal protection against extreme cold can be purchased (buying better winter clothing, using taxis on cold days, etc.) we investigate how temperature sensitivity relates to a proxy for subject income. To probe biological adaptation to cold conditions we (a) compare the sensitivity to treatment of domestic students with those from overseas (in particular from a set of hot countries) and, (b) examine how the sensitivity of the latter group evolves with repeated exposure.

We find a negative impact of outdoor temperature on indoor performance. The effect is substantial. In our preferred specification, which includes student fixed effects, year fixed effects, and controls for other weather conditions, a ten degree (1.75 standard deviations) Celsius colder outdoor temperature on exam day causes a reduction of about one-twelfth (8.09%) of a standard deviation in performance. The magnitude and significance of the effects prove highly robust to a wide range of tests. We speak to issues of mechanisms indirectly by characterizing the (less-than-complete) efficacy of adaptive strategies at various levels. While our study relates to adults taking university-level exams, such performance effects might be expected in a wider range of mentally-demanding tasks in the workplace.

The rest of the paper is organized as follows. In Section 2, we review some pertinent existing research. In Section 3, we detail our administrative and weather data. Section 4 presents our identification strategy. Section 5 details our main results. Section 6 explores cumulative effects of cold. Section 7 details results on adaptation. In Section 8, we challenge the robustness of our results. Section 9 concludes.

## 2. Literature: A selective review

Temperature is increasingly recognized as an important factor in many outcomes of interest to economists. The effect of temperature realizations on productivity have been characterized at the economy level by Dell et al. (2012), United States county level by Deryugina and Hsiang (2014) and plant-level by Zhang et al. (2018). Recent papers have found effects of hot weather on human outcomes including morbidity (Bleakley, 2010; Schwartz et al., 2004), mortality (Barreca et al., 2016; Burgess et al., 2017), productivity (Somanathan et al., 2015) and decision-making (Heyes and Saberian, 2019). In such studies, the temperature observations have typically fallen in the range above 25°C, implying little or no power to uncover impacts of low temperatures.[3]

*2.1. Temperature (especially cold) and mental function*

Among research linking outdoor temperature to cognitive performance, such as Graff Zivin et al. (2018), find that short-run changes in temperature negatively impact the cognitive performance of children above 26°C but find little evidence of longer-run effects.[4] Park (2016) studies children taking standardized exams in a panel of New York City schools during the month of June. He finds that performance is compromised by 0.22% per 1°F (0.55°C) rise above 72 F (22.2°C). Goodman et al. (2018) focus on longer run effects of hot weather across the school-year, finding that each 1°F increase in school year temperature reduces the amount learned that year in U.S. schools by about 1%.

Zivin et al. (2018) use data from the fixed date of the National Chinese Entrance Exam to estimate the effects of outdoor temperature on cognitive performance. They find that, in a setting without air conditioning or the ability of students to sort by location, a 1°C increase in summer temperatures (mean of 23.2°C) reduced performance by 0.029 standard deviations.

Research on the effects of cold temperature on mental performance and productivity is less developed. With one notable exception, the evidence that does exist relates exclusively to *contemporaneous* temperature. In other words performance and behavior *during* exposure. Pilcher et al. (2002) provides a meta-analysis and Taylor et al. (2016) a survey.

Without identifying a mechanism, various experimental studies have shown that contemporaneous exposure in the range - 20°C to 10°C can reduce memory function (Thomas et al., 1989; Patil et al., 1995), consistency of decision making (Watkins et al., 2014), and speed in pattern recognition and number comparison (Banderet et al., 1986). Studying driving behavior in cold conditions, Daanen et al. (2003)

[3]Lee et al. (2014) regress outdoor temperature on speed of completion of a routine clerical task by bank employees in Tokyo. They find a negative and significant coefficient on their quadratic temperature term, consistent with a *positive* impact of either extreme heat or extreme cold on productivity. However; (1) The mean and standard deviation of outdoor temperature in the table of summary statistics are 17°C and 5°C respectively, suggesting few observations in the temperature range of interest to us. (2) The authors do not allow for the possibility of asymmetric impacts of heat versus cold by (for example) applying non-parametric methods.

[4]They explicitly acknowledge that they can speak to high temperatures only: "Since these tests were predominantly given during the warmer periods of the year, our analysis of short-run temperature effects will only be informative for temperatures in this range" (Graff Zivin et al., 2018, p.84). In their dataset, for example, the mean temperature on day of test is 22.5°C and standard deviation 4.9.

note that cold can impair mental function and thus increase accidents, observing a 16% decrement in performance of drivers in simulated conditions at 5°C compared to 20°C.

There are several channels that might link cold to compromised cognitive performance. In their survey, Cheung et al. (2016) emphasizes the depleting effect of thermoregulation. The initial response to short-term cold exposure is cutaneous vasoconstriction, reducing blood flow to the skin and extremities. This serves to decrease the thermal gradient between the body and environment. While this is effective in maintaining body core temperature, it simultaneously causes discomfort. As exposure persists, heat maintenance requires the depletion of limited carbohydrate stores (Bell et al., 1992) which has been shown to decrease manual dexterity, motor coordination, work tolerance, and "perceptual discomfort that can effect cognition" (Cheung et al., 2016, p.155). Exposure to cold conditions also alters the concentration of central catecholamines in humans which has been linked to "... a detrimental effect on cognition as brain regions such as the prefrontal cortex are reliant on these neurotransmitters for normal function, ... (as such) there is a plethora of evidence which demonstrates that tyrosine supplementation improves cognitive function during acute cold stress" (Taylor et al., 2016, p.372). Breathing very cold air can also irritate the human respiratory system, potentially damaging mood (Hartung et al., 1980), while even brief cold exposure can elevate hormonal stress markers (LaVoy et al., 2011).

A parallel body of research highlights the role of psychological mechanisms. Consistent with the classic "distraction theory" of Teichner (1958), cold conditions may provide alternative stimuli and thus interrupt focus which would otherwise be applied to the cognitive task in hand ("*i.e.,* attention is focused on feeling cold rather than competing the cognitive task provided" (Taylor et al., 2016, p.372). Uncomfortable temperatures might also influence motivation and performance via their negative effect on mood or sentiment (see citations in Noelke et al. (2016)). The case for the importance of psychology is reinforced by studies such as Rai et al. (2017), which show that the attitudes and behaviors of experimental subjects can even be influenced by temperature *cues*, such as photographs of cold places.

While such studies are suggestive, they offer little help in understanding what the wider impact of cold outdoor temperature might be across the economy, since the vast majority of mentally-taxing work in cold countries is done indoors. Indeed, in most industrialized countries the median adult spends more than 90% of their time indoors, particularly during cold weather (Nguyen et al., 2014). Nguyen et al. (2019) finds similar effects for children, as when especially cold weather occurs more time is spent inside.

To our knowledge, the only study examining the sustained impairment due to cold exposure after stimuli is removed is Muller et al. (2012). They track a sample of 10 young adults during *and after* being cooled in a temperature-controlled chamber at 10°C. Working memory, choice reaction time and executive function declined during exposure, and impairments sustained an hour after exposure. This points to the possibility of the impact of exposure to outdoor cold being something that the subject imports when they move indoors. Relatedly, Heyes and Saberian (2019) argue that uncomfortable outdoor temperature might affect indoor performance *even if the subject is not directly exposed to it.* For example, extreme cold may prevent or discourage subjects from going outside to 'stretch their legs'. Lack of fresh air has been linked experimentally to outcomes such as decreased mental function (Chen and Schwartz, 2009) and depressive mood (Cunningham, 1979).

### *2.2. Adaptation*

Adaptation to cold outdoor temperatures might occur at various levels (for example national, municipal, organizational, individual) and over time. In this paper, we present short-run analyses that will net out avoidance measures that are based on historical climate, such as locational sorting, technology adoption and building design.

The first and most obvious short-run protection against cold weather is to move indoors. The extent of protection afforded by a building plausibly depends on the effectiveness of its interior heating. At the other end of the temperature spectrum, the analogous protective benefits of air conditioning have been explored in a number of studies. Park (2016) study New York City children taking Summer exams, and does not find a significant protective benefit to air conditioning. He does note that of schools with air conditioning installed, up to 40% were deemed defective by an independent survey. In contrast, Goodman et al. (2018) finds that school level air conditioning offsets most of the potential learning decrement due to heat.[5]

A related literature studies the mitigative effects of other 'technologies', such as investment in high quality winter clothing (Mäkinen, 2007). We will explore pecuniary channels of self-protection later.

Biological adaptation may also be physiological or psychological, though evidence on each is comparatively scarce. Teichner (1958) developed the concept of

[5] Goodman et al. (2018) uses a triple-difference strategy combining within-student observations with within-school variation status in cooling status over time. The only threat to such an approach is the possibility that the timing of A/C installation was correlated with other unobserved improvements in learning environment.

*psychological cold tolerance* "... which was conceived as depending largely on the individual's familiarity with cold and on his anxiety level. These are factors reflected in the individual's subjective reactions which should not be ignored when discussing performance in the cold." (Enander, 1984, p.370). In terms of such habituation there is some evidence of changes in attitude to cold after repeated exposure. In early work, Fine (1961) showed that subjects evaluate 'cold' less on a cold-warm scale after repeated exposure. Enander et al. (1980) compared the response to cold of subjects accustomed to working in cold conditions (meat cutters) against office workers. While there was no difference in physiological response, they found evidence consistent with psychological adaptation. The accustomed group experienced significantly less cold sensation and pain than the unaccustomed group. Another study consistent with physiological adaptation is Tochihara (2005), who found that the rectal temperatures of a sample of coldstore workers fell less when exposed to a temperature of -20°C for 60 minutes than did those of the control sample.[6] Several studies have found evidence consistent with increased brown adipose tissue ('brown fat') among those exposed to frequent cold (for example Blondin et al. (2014)).

Overall, the bulk of the evidence points to a primarily psychological adaptive process to cold. This provides an interesting contrast to the analogous evidence on adaptation to heat exposure. "(T)he evidence of physiological adaptations from longitudinal cold exposure is equivocal (Launay and Savourey, 2009), while the dominant adaptation is a perceptual habituation and desensitization to cold stress rather than large-scale systemic physiological changes of the sort seen with heat acclimatization" (Cheung et al., 2016, p.155).[7]

### *2.3. Projected change in cold*

It is commonly assumed that as climate warms, the distribution of daily temperatures will see a rightward shift towards warmer averages. In isolation, this would

[6] Brazaitis et al. (2014) immersed 10 male subjects in 14°C water and timed how long it took for body temperature to drop to 35°C. On day 1 the average cooling time was 130 minutes, on day 14 cooling time had fallen to 80 minutes. The authors suggest a reduction of temperature gradient as a possible adaptation to cold.

[7] The abstract in the survey of physiological adaptation by Daanen and Van Marken Lichtenbelt (2016) ends: "Dedicated studies show that repeated whole body exposure of individual volunteers, mainly Caucasians, to severe cold results in reduced sensation but no major physiological changes. ... (H)uman cold adaptation in the form of increased metabolism and insulation seems to have occurred during recent evolution in populations, but cannot be developed during a lifetime in cold conditions. Therefore we mainly depend on our behavioral skills to live in and survive the cold" (Daanen and Van Marken Lichtenbelt, 2016, p.104).

indicate that problems of extreme cold temperatures may be alleviated due to warming temperatures. However, while this turn out to be the case in many places - in which case the effects that we uncover in the paper will deliver a previously unaccounted for benefit of climate change - in others it will not.

Hansen et al. (2012) showed that the chances of unusually cool seasons have risen in the past 30 years, coinciding with the observed rapid global warming. One mechanism through which this has been studied is a weakening of the polar vortex, which makes easier the periodic southerly movement of cold Arctic air masses. Kolstad et al. (2010) and Kretschmer et al. (2018) show that in the past several decades the frequency of weak polar vortex states has increased, which has been accompanied by subsequent cold extremes in the mid-latitudes, including North America, Europe and northern Asia. Kim et al. (2014) find evidence linking weakening of the vortex to Arctic sea-ice loss, consistent with the trends associated with climate change. "A handful of studies offer compelling evidence that the stratospheric polar vortex is changing, and that this can explain bouts of unusually cold winter weather (in North America)" (Francis, 2019).

## 3. Data

We obtained administrative data from the university as the basis for our measure cognitive performance. In particular, we observe the universe of grades achieved by undergraduate students for over 1.2 million courses. Our sample includes students who first enrolled for a course at the university in or after the Fall semester of 2007, and the latest courses we observe are those examined in December 2015. We connect this dataset with institutionally provided student information such as gender, age and address. Data on financial status by six-digit postal code comes from the 2016 Canadian Census of Population.

The academic year is split into two semesters. Fall-semester courses are taught from September through November, with final exams written in December. Because of our interest in cold we use these grades (N = 638,238) and the students that achieved them (N = 66,715) as the basis for our analysis.

That course-level grade is our dependent variable introduces a complication. While we hypothesize that exam day temperature impacts performance in the final exam, assessment for each course is based only partially on final exam performance. Other elements such as midterms or coursework completed during the semester also contribute. Academic regulations require that final exam weight be no lower than 40% and no higher than 60%. The variation in weighting adds measurement error to the dependent variable which is uncorrelated with our regressor of interest.[8] While such measurement error does not bias OLS estimates, it increases the associated standard errors making significance claims conservative. It also requires that in interpreting effect sizes, we use a multiplier to reflect that any impact of exam-day temperature on exam performance has a dampened impact on course-level performance. In our main specifications we impute the variation in exam performance as a factor of two times the variation in course performance, consistent with the assumption that the final exam carried 50% of the weight in every course. In doing so, a 5% decrement in overall course score maps to a 10% decrement in final exam score.

Daily meteorological data comes from the nearest Environment Canada weather station that provided consistent data across out period (Station ID 6105978) located 5.1 km from the centre of the campus. There is wide variation in the outdoor temperatures experienced by students on exam days, illustrated in Figure 1.

Summary statistics relating to course performance, student characteristics and weather are in Table 1. The average course grade is 71.98%, corresponding to a 'B' in the university grading scheme. Grades vary considerably within-student, the standard deviation is 10.31%, or two letter grades around the mean. Exam days are cold, averaging -5.13°C. Temperatures also vary considerably within-student, as a one standard deviation colder temperature is -10.81°C while a one standard deviation milder temperature exam day is above freezing. There is often snow falling (the equivalent of 2.12 cm)[9] and snow already on the ground (2.46 cm). Female students account for 60% of the data while foreign students contribute 7.43%. We use a total of 638,238 exams, written by 66,715 students. The succeeding columns present summary statistics by gender and foreign status.

## 4. Methods

In this section we detail the identification strategy used to estimate the causal impact of outdoor exam temperatures on indoor cognitive performance (imputed exam score).

Identification comes from quasi-random assignment of exterior temperatures to exam days. Fall semester exams are held in an exam period that runs from early in December until the university closes for the Christmas recess. The earliest and

[8] The granularity of course grade reporting is an additional source of measurement error. Final course grades are recorded as letters, which correspond to a score interval. For example, an 'A' corresponds to a score in the interval 85-89%, which we then assign to the midpoint of its interval.

[9] Environment Canada uses a 10-to-1 conversion of water equivalent precipitation and snowfall.

latest dates on which we observe exams in our sample are December 4 and December 21. Exams are held in one of three time slots (beginning at 9:30 am, 2 pm and 7 pm).[10] The university releases the exam schedule in mid-October, much later in the semester than the final class enrolment deadline (mid-September).

Our results use a student fixed effects model estimated by Ordinary Least Squares (see, for example, Ebenstein et al. (2016)). Our main specification is:

$$Grade_{i,t} = \beta_0 + \beta_1 * Temperature_t + \Delta_t + \gamma_i + \eta_y + \epsilon_{i,t} \tag{1}$$

Where $Grade_{i,t}$ is the imputed exam performance for individual $i$ taking a course where the final exam took place on day $t$. Our parameter of interest is $\beta_1$, the coefficient of mean outdoor temperature on the date of exam. We explore the robustness of our estimate using alternative temperature measures later. The standard errors are clustered at the student level. Later, we demonstrate that results are robust to a number of other plausible clustering strategies.

The inclusion of student ($\gamma_i$) and year ($\eta_y$) fixed effects implies that identification comes from within-student and within-year variation. In other words, variations in the performance of individual subjects under alternative temperature treatments, within an exam period. Year fixed effects capture changes to course grades between years that are common across students including, for example, grade inflation.

$\Delta$ is a vector of exam-day controls – precipitation on exam day and its interaction with temperature, relative humidity, snow on ground, windchill, day of week indicator variables and the date-in-month.

Inclusion of the interaction term between temperature and precipitation in our specifications reflects the common observation that damp cold may have a different effect than dry cold. For the same reason relative humidity is included as an additional control in our preferred specification.[11] The interpretation of $\beta_1$ is the effect of a 1°C change in exam temperature on a dry day. There is zero precipitation on 45% of the days in our sample, and less than one millimeter of precipitation on 62% (see Figure A2 for a full distribution). A robustness exercise shows that effect sizes

[10] We do not observe students allowed to defer an exam to a date other than that mandated for the course, typically about 4% of the total. Deferment for reasons unrelated to temperature (family bereavement, religious holiday, etc.) are of no concern. Insofar as some deferments result from low exam-day temperature it is plausible that it works against the direction of any effect that we find, since postponement from a day that is unusually cold is likely to be to a later date that is less cold. However this is a valid caveat to hold in mind. Note that the university as a whole never closed on a regular business day or canceled an exam for weather-related reasons during the study period.

[11] We report the estimates of precipitation, temperature × precipitation and the other controls in Table A1.

sustain even when we estimate on dry days alone. We also present estimates without precipitation, or its interaction, in an appendix.

Precipitation in December almost always means snow at this location. In addition to precipitation actually falling on a particular day, we also include accumulated snow on ground (measured by Environment Canada's acoustic sensors such as the SR-50A). Accumulated snow might effect ease of travel, although it is worth noting that the municipal government exerts considerable efforts to the clearance of snow from sidewalks and streets in the city, as does the university on its campus. Actual experience of snow under-foot in the vicinity of a downtown location such as the university campus is likely quite different to conditions at the weather station.

Day-of-week fixed effects capture the possible effects of exam timing while date-in-month (as a continuous variable) captures any variation in exam performance correlating to *when* in the month an exam takes place. For example, including date-in-month helps if "difficult" courses tend to have exams scheduled later in the month, or if proximity to the holidays has an effect on exam performance.

In a supplementary analysis we explore the possibility of a non-linear relationship between outdoor temperature and indoor performance. To do this we estimate two models. First, our continuous temperature regressor in Equation 1 is replaced by a series of indicator variables corresponding to bins of width 2.5°C. Second, we use a series of indicator variables that organize temperature treatments into deciles.

## 5. Results

### 5.1. Basic plot

Figure 2 provides a simple plot of exam day temperature and exam performance, after adjusting only for year of exam. The size of markers is proportional to the number of observations in each 0.5°C bin.

Visual inspection suggests a positive association between performance and exam day temperature. We formalize this by plotting the line of best fit estimated by OLS with only year fixed effects.

While the absence of plausibly important controls means that such a plot and associated fitted line should be treated with caution, these initial effect sizes are substantial and prove robust to the inclusion of controls and their associated alteration of the temperature coefficient's interpretation.

### 5.2. Linear

Our main results are reported in Table 2. The dependent variable is expressed in hundredths of a standard deviation of exam score. Standardization of grades is across all years and students.[12]

Column 1 presents our sparsest specification, containing student and year fixed effects and accounts for precipitation and the precipitation $\times$ temperature interaction.[13] Column 2 adds controls for day-of-week. Column 3 controls for date-in-month. Column 4 through 6 add relative humidity, accumulated snow on ground and windchill, respectively.

In each column, the estimated coefficient on temperature is positive and statistically significant beyond the 1% threshold. Coefficient values are also stable across specifications. Column 6 presents our preferred specification, corresponding to Equation 1.

The coefficient on temperature is 0.809***, suggesting that for every 1°C increase in exam day temperature, performance increases by 0.00809 standard deviations.[14] The 90th and 10th percentiles of the temperature distribution in the sample are 2.2°C and -14.7°C respectively. Hypothetically moving from a day at the 90th percentile in terms of temperature, to a day at the 10th percentile, delivers a decrease in temperature of 16.9°C. According to our preferred estimate this causes a substantial decrement in exam performance of 0.14 about one-seventh of a standard deviation. Equivalently, to deliver a reduction in performance of 0.1 or one-tenth of a standard deviation would require a 12.4°C decrease in outdoor temperature.

### *5.3. Non-linear*

In Table 3 we repeat the exercise just described but replace the continuous measure of exam day temperature on the right-hand side of Equation 1 with a series of eight indicator variables. Each takes the value 1 if average temperature on exam day $t$ fell in the range that defines the associated indicator's bin. Bins are constructed to be 2.5°C in width, built out from zero. The bin containing days with temperature below -15°C is the reference (omitted) category.

[12] In Table A5 we standardize by year and course to find similar estimates.

[13] In Table A1 we also report our analysis without precipitation or its interaction with temperature. We then report the coefficient of precipitation and its interaction with temperature, and find both are negative and statistically significant. A specification in which we drop *all controls* is reported as a robustness exercise in Table 11, and delivers a main coefficient of 1.526***.

[14] It is possible that exam markers adjust their grading standards in response to the quality of responses in a particular pile of scripts. Insofar as that is the case it seems likely that the correlation between grading stringency and response quality is positive (the marker would apply laxer standards if she found the students performing poorly). This would imply that our estimated coefficient would understate the true effect size, making inference conservative.

Each column in Table 3 replicates the combination of controls in the same-numbered column in Table 2. The preferred specification is again reported in column 6. The coefficients for each bin are broadly consistent across columns, suggesting that estimated non-linear effects are also robust to the inclusion of alternative control sets. The coefficients and associated 5% confidence intervals from the sparsest (column 1, left panel) and preferred specification (column 6, right panel) are plotted in Figure 3.

Figure 3 shows a negative impact of cold outdoor temperature on performance, which is roughly linear over the range that we study. The vertical axis scale in both figures is hundredths of a standard deviation. For example, in the right-hand panel of Figure 3, moving from a day in the 0°C bin to the -15°C bin reduces course grade by about 12% of a standard deviation.

While the overall trend seems to be roughly linear, here we note two interesting artifacts of Figure 3. The first is that the -15°C to -12.5°C temperature bin has an estimated effect that is worse than the colder temperatures below -15°C. We are relieved that when the data is divided in another reasonable manner (into deciles in Table A2 and Figure A1) we find results broadly consistent with those in Figure 3 while removing this anomalous negative effect for that temperature range. Second, exams with temperatures above zero seem to have disproportionately better results, suggesting we could enrich our specification with a kink. In Table 11 we winsorize our temperatures beyond the 0°C mark and find no meaningful differences to our main estimates.

*5.4. Heterogeneity*

In this subsection we investigate heterogeneity of effect size by sex, ability, and foreign status of the student. To do this we add to the preferred specification, in separate exercises, interaction terms between temperature and an indicator variable for the subsample in question. The results of these exercises are reported in Table 4.

In column 1 we interact temperature with an indicator that takes value 1 if the student is female. The estimated coefficient of 0.927*** is for a male student. The negative and significant interaction term implies that ceteris paribus female students are about twenty percent less sensitive to cold, consistent with research that has found women wear both more layers and more articles of clothing in cold weather, regardless of activity (Donaldson et al., 2001).

In column 2 we conduct the same exercise but with an indicator that takes value 1 if a student arrived at the university with an A (or 80) admission average. This applies to 43% of our sample of exams. The coefficient on the interaction term is large in value, -0.311***. The central estimate suggests that these high-admission students are roughly one third less cold-sensitive than their counterparts. This is not surprising given that most domestic (Canadian) students that admit as high achieving have already demonstrated an ability to perform well in winter examinations under comparable outdoor conditions in the context of their secondary school education, prior to attending university.

In column 3 we conduct the same exercise on foreign students, using domestic students as a baseline. Classification as foreign student is derived from paying international student fees to attend the university, or through immigration status. Perhaps unsurprisingly, foreign students are around 60% more sensitive to cold than domestic students. Almost all foreign students come from countries that are substantially less cold than Canada, and so are unlikely to be accustomed with such temperatures. We provide evidence of habituation or biological adaptation by investigating the performance of foreign students, both on arrival and through time, later.

## 6. Cumulative effects

While not our main focus, before turning to adaptation we investigate effects of temperature not just on the exam day, but during the preceding teaching semester.[15]

To do this we add to our preferred specification, a proxy of the total 'cold' experienced in the 30, 60 and 90 days prior to the exam. The measure that we use for cumulative cold is total heating degree days (HDD) over the period in question. A HDD is the number of degrees that the average temperature on a particular day is below 18°C, and is the standard measure used to quantify cumulative demand for heating in buildings. For example, if in a 30 day window half the days have an average temperature of 12°C while the other half have an average temperature of 17°C, the total HDD count over that 30 day window would be (15 x 6) + (15 x 1) = 105.

Table 5 reports the results of these three exercises. Columns 2, 3 and 4 include the total HDDs in the 30, 60 and 90 days prior to first exam, respectively.[16]

The results in this table are interesting for two reasons.

First, as a robustness check on our main result. The coefficient on our primary independent variable of interest, same-day temperature, is stable across columns.

[15] Evidence of the cumulative effect of temperatures on cognitive performance is mixed. For example, with respect to much warmer temperatures Goodman et al. (2018) found no cumulative effect of temperature on learning in United States schools with A/C.

[16] In Table A3 we use average temperatures leading to exam day, the results are similar.

This suggests that we have isolated short from longer-run temperature effects. A potential challenge to our main specification is that temperature on exam day may be correlated with how warm or cold it had been in the lead up to the exam, such that failing to control for the latter would bias (or completely explain) our central estimates. Comparison of the columns in this table discourages the view that any such bias has substantially distorted our results. To ensure that this is not an artifact of the HDD measure, we report the results of analogous exercises using either average temperatures or much shorter pre-exam windows in Appendix Tables 2 and 3. We find our coefficient of interest is little-disturbed.

Second, in each of columns 2 through 4 the estimated coefficient on the pre-exam history of HDD is statistically significant. Temperature during the semester appears to have a significant impact on how students perform. However the sign is *positive*, implying cooler temperatures across the teaching term are associated with improved performance. This is consistent with previous literature that finds unappealing outdoor temperatures can encourage substitution from outdoor leisure to indoor 'work' (Graff Zivin and Neidell, 2014). For example, in column 2, if each day in the 30 leading up to the exam were one degree warmer, that would roughly offset exam-day temperature being one degree colder.

Another consideration could be cold temperatures leading to student sickness. While we do not have case-level data of, for example, admissions to the university clinic, we do analyze how short run temperatures leading up to the exam affect performance in Table A3. We find previous 1,3, and 5 day average temperatures leading to the exam have mixed signs and statistical significance. We note that this measure is imperfect and see examining the relationship between cold and sickness as a possible avenue for future research.

## 7. Adaptation

Central to any analysis of the costs of climate change is understanding the efficacy of adaptation. Analyzing adaptation also speaks indirectly to mechanisms that might underpin the effect that we have identified. We explore adaptation at three different levels.

### *7.1. Organizational*

There are two temperatures that might influence how a worker performs, namely indoor and outdoor. The employer can control the former, but not the latter.

There are two separate questions that research in this area can address. First, to what extent is the technology of climate control effective in decoupling indoor from outdoor temperature. Second, insofar as is it does lead to full or partial decoupling, to what extent does that mitigate the causal effect of outdoor temperature on the outcome variable of interest.

With respect to hot temperatures, recent studies provide evidence of only partial mitigation by air-conditioning. These share two important limitations. (1) Installation and quality of air-conditioning is unlikely to be randomly-assigned, and in many settings is plausibly correlated with unobserved characteristics (such as financial circumstances) of the school, business or other organization that might impact effect size through other channels. (2) To our knowledge, the actual efficacy of the cooling technology is unknown.[17]

Winter heating in Ottawa public buildings is good, perhaps not surprising given that very cold temperatures are common. Employers in Ontario (including universities) are obliged by law to maintain a workplace temperature above 18°C. In light of this, internal temperatures experienced by our subjects are plausibly uncorrelated with outdoor temperature by design. However we tested this directly by working with campus building managers to measure and collect data on daytime interior temperature. The sample was collected during December 2018 for the 28 most important exam rooms by contribution to sample. Matching with outdoor temperature on the same day, we investigate the links between indoor versus outdoor temperature in exam rooms.

The data collected for Montpetit Hall Room 021 (MNT021) is presented in Figure 4. This is the largest room by contribution to sample, contributing 66,888 of the 638,238 observations that we use in our regressions. There are two important features of this plot. First, there is little variation in indoor temperature, fluctuating between 21.5 ±0.3°C (reference lines at ±1°C of the room average are provided). Second, such variation as does exist does not look to be meaningfully correlated with outdoor temperature.

Figure 5 presents analogous diagrams for each of the 28 rooms (MNT021 is third

[17] Quinn et al. (2014) and Tamerius et al. (2013) present survey evidence on the relationship between indoor and outdoor temperatures in a sample of 327 buildings in New York City. For outdoor temperature ranges above 15°C they find a correlation between outdoor and indoor temperature to be 0.64 (Tamerius et al., 2013, Fig.1) despite air-conditioning penetration in that city at time of sample being 87.5%. Interesting given our focus is that for temperatures below 15°C the correlation coefficient between indoor and outdoor temperature is just 0.04. In general, heating space is easier than cooling it. In addition, modern air-conditioners are characterized by a 'temperature drop' - the maximum by which the refrigerant coils can reduce incoming to outgoing temperature - which for most common designs is less than 20°C. Even if working to its full potential, this places a bound on how cool the air-conditioned space can be kept when outdoor temperatures are very high.

from the left, second row). In each case we superimpose horizontal reference lines at the room's average temperature $\pm 1°C$. The figure tells us that all exam rooms are not equal in terms of the consistency with which internal temperature is maintained. In some rooms internal temperature fluctuates outside the $\pm 1°C$ corridor, though even in these 'leaky rooms' there is little suggestion of correlation between outdoor temperature and what is going on outside.

We conduct two further exercises to test whether our central results are driven by imperfect climate control.

First, we test the role of building age. Our sample includes both new and old buildings. For example, Tabaret Hall (TBT) was constructed in 1856. While spaces are well maintained, there is a concern that our results are driven by older buildings that do not meet modern standards. To explore this we divide buildings into two categories, 'New' (those completed after the year 2000), and 'Old' (the rest). This roughly splits our sample in half. Column 1 of Table 6 reports the results of adding to our main regression an interaction term that between exam-day temperature and an indicator variable that takes the value 1 if the exam room is located in a new building. The interaction term is negative, and marginally significant, consistent with our concerns. The estimated coefficient on temperature (0.837***) is now interpreted as the effect of temperature on performance for exams written in an old space. Writing in a new building is estimated to offset about 14% of the outdoor temperature effect.[18]

Second, we exploit the room temperature measurements reported in Figure 5 directly. Even within a building some rooms may be better temperature-controlled than others. In column 3 of Table 6 we report the results from running the specification from column 2 but excluding the exams taken in rooms identified as 'leaky' in Figure 5 (that is, those with temperature observations outside the $\pm$ 1°C band). Under this restriction the coefficient of the new building $\times$ temperature interaction term becomes much smaller and far from statistically significant at conventional levels.

Taken together, the evidence in this subsection supports our conjecture that the most obvious technological adaptation that an organization can use to protect employees against cold, namely climate control, is relatively fully-exploited. As such, the effects that we identify should be understood as already accounting for that base margin of protection.

[18]For completeness we repeat the specification in column 1 but including course level fixed effects, as there may be a relationship between building age and course level. This is reported in column 2 in Table 6. The additional inclusion does not change results, and increases the statistical significance of the new building and temperature interaction term.

### *7.2. Individual*

Individuals plausibly have ways in which they might protect themselves privately from cold. We explore two. One approach is to reduce exposure by reducing commuting time. Another is spending on personal protection.

First, we examine the extent to which our effect dissipates with proximity to campus. We note that residential location and commuting time is not randomly assigned in our setting. Students might reasonably be assumed to take account of climate when deciding where within the city to live, and results in this section need to be interpreted with that in mind. We add to the preferred specification a control for distance between campus and term address as recorded in the student record ('Distance'). We then linearly interact distance with exam day temperature. For completeness, we also add the interactions between distance and precipitation, and between distance and accumulated snow on the ground. The results are presented in column 1 of Table 7. The estimated coefficient of temperature $\times$ distance is 0.000 and not statistically significant, suggesting no protective effect of proximity. That is, as a student moves closer to the university there is no reduction in the sensitivity of their performance to outdoor temperature. Reassuringly, the coefficient on the primary temperature regressor is not meaningfully disturbed.

An issue about the exercise just described is that we observe two distinct addresses for each student. First, an enrolment address used during a student's application to the university. This is almost always the parental or home address. Second, the term address that students are encouraged to keep updated. For some, the application address will be where they actually live, for some it will not, and the lack of variation reflects a failure to update personal details rather than a lack of relocation.

Ideally, we would like a sample of students for which we know where they live with some additional assurance. We construct something close to this in two ways. First, we identify those students who have a term address *distinct* from that at enrolment. We call these students 'movers'.[19] Second, we identify those students who are non-movers but for whom the application address is within 10 km of the university campus. These students live within ready commuting distance of the university and in most cases live at home during their studies, something that is common amongst Canadian undergraduates.

Column 2 reports the results from movers and column 3 from non-movers with an enrolment address within 10 km of campus. The main temperature coefficient of interest remains similar across the three samples, and in each case is statistically

[19]While it is possible that some families might move in the period between receiving offer and the start of studies, this number is likely small.

significant, despite much eroded sample sizes in column 2 and 3. The coefficients on the temperature × distance interaction are small and insignificant at conventional levels, discouraging the view that proximity alone delivers a meaningful protective benefit.

In Table A4 we present results of a different approach. We stratify by distance the sample of students who report a term time address within 20 km of campus, irrespective of whether or not they are in our movers sample. In most cases the address that we use is likely the student's residential address. The estimated coefficient on temperature is stable across columns, even in column which estimates only on students who are 'currently' living within 2 km of campus.

Subject to the caveats already noted, the exercises presented in Tables 7 and A4 provide no indication that living close to place of work mitigates the effect of outdoor cold on performance. To the extent that distance correlates with direct exposure to outdoor temperature this implies that it is not the 'amount' of direct exposure which drives the decrement in performance. A similar impact of cold weather is seen even among those who live close to campus. This is more consistent with psychological rather than physiological mechanisms, or other channels identified that do not depend primarily on exposure length.

Apart from locational choice, there may be pecuniary ways in which individuals may mitigate the effects of weather to their person. For example, a student may invest in better quality winter clothing, or avoid waiting for a bus by using taxis on particularly cold days. Here we explore a possible role of affluence in temperature-protection.

We do not directly observe the financial circumstances of our sample. However we do know the address reported at first enrolment, which is likely the parental or home address. As a proxy for financial circumstances, we use the average income level at the associated six digit postal code at enrolment as measured in the 2016 Canadian Census. We add this to our preferred specification as an interaction term only, as the student fixed effect will already have accounted for individual income. We present these results in Table 8.

In column 1 we work with all students, including foreign students, provided they had an eligible six digit postal code at enrolment. Because there exists the possibility that the Canadian address reported for a foreign student may a poor indicator of familial wealth, we restrict our sample to domestic students in column 2. In either specification, the main coefficient remains positive and significant. It is somewhat larger than in Table 2, and is now interpreted as the effect on a student from an enrolment address in a hypothetical postal code with average household income of zero dollars. The negative and significant coefficient on the temperature × average income interaction indicates a protective effect of family affluence. Each 10,000 CAD increase in average household income in postal code of origin is associated with a 3.7% reduction in the sensitivity of a particular student to cold. A histogram of household incomes is presented in Figure A5. Compared to a zero income benchmark, a student coming from a postal code in the modal category (namely 40,000 to 50,000) benefits from a roughly 15 - 19 % mitigation of cold sensitivity.[20]

Overall these exercises are consistent with a protective, but still less than complete, effect of family affluence.

*7.3. Biological*

In this section we present evidence consistent with the results of small scale studies of physiological or psychological adaptation to extreme temperatures mentioned in Section 2. We do this by looking in more detail at the cold-sensitivity of students from other countries and how they evolve over time.

In Table 4 we established that foreign students were statistically more cold-sensitive than domestic students. That Canada is a cold country implies that most students from abroad are from warmer climates. Despite our data not including country of origin at the student level for privacy purposes, we construct a subsample of students most likely to be 'hot' countries by leveraging their language of instruction. The University of Ottawa is the largest bilingual English-French university in the world and many undergraduate programs can be taken in their entirety in both languages. As part of its cultural mission the university encourages applications by students from countries of the Francophonie through substantial fee reductions, scholarship programs and promotional efforts.[21] 41% of foreign students use French as their language of correspondence with the university. Without knowing individual-level country of origin, the overwhelming majority of non-domestic come from the nations of French Africa (Cote d'Ivoire, Senegal, Cameroon, etc.), or the French Caribbean (Haiti, Dominican Republic etc.) at the aggregate level. These are all hot countries with winter low temperatures typically 25 to 40 degrees Celsius warmer than Ottawa. We identify these students in two ways. First, we construct a sample comprising foreign students that elect to study entirely in French across all four years of their program ('Method 1'). Second, reflecting that many students

[20]Caution should be used in interpreting these results, as the astute reader would note a linear model predicts an income of 267,838 CAD would perfectly offset, and above that reverse, the effects of cold. While we do not see such wealth in our data due to measurement at the postal code (rather than individual) level, it is reasonable to assume that there are diminishing returns to wealth.

[21] For example foreign students from French-speaking institutions pay domestic rather than foreign fees, which for 2014 - 15 implies a reduction from 22 600 CAD per year to 6,800 CAD.

who arrive as unilingual French will develop their English-language skills sufficiently to take at least part of their later studies in English, we relax the sample criterion to comprise foreign students that elect to study only French-taught courses in their first year ('Method 2').

Column 1 in Table 9 reports the result of estimating our preferred specification on the Method 1 subsample, with column 2 estimated on remaining foreign students (most of which come from China and the United States). We can see that the effect of cold on hot country students is much larger than even the effect on international students in general (column 2). The central estimate suggests that a 10°C reduction in outdoor temperature causes a decrement in performance of almost half (45.9%) of a standard deviation. The results in columns 3 and 4 are those estimated on the subsample constructed on the basis of Method 2. They are consistent, though the implied decrement in performance for a 10°C reduction in outdoor temperature is somewhat smaller at 29.9% of a standard deviation.

The results presented to this point have been based on within-student variation in performance under different temperature treatments across their entire period of study. Here we explore how the performance of arrivees changes over time.[22]

The results in Table 10 are estimated only on exams taken during the first year of enrollment. Because this specification incorporates a temperature × foreign interaction term, the estimated coefficient on temperature, 1.124** represents the effect of temperature on a domestic students, within a course level, during their first exam season. That the coefficient on the temperature × foreign interaction regressor is positive and significant confirms the earlier finding that foreign students are much more cold-sensitive in their first year.

This exercise is important for another reason. If cold winter temperatures directly affect student attrition rates, then in all specifications we are estimating on temperature 'survivors'. Our results could then be attenuated, particularly at upper course levels. By estimating column 1, we better approximate the effect of cold on performance absent students self-selecting out during the course.

Column 1 is estimated on all students, irrespective of whether they graduate. In column 2 we conduct the same exercise, looking at courses taken in first year of enrollment, but now *only by those students that ultimately graduate*. This is more akin to a balanced panel estimate than the earlier results, and addresses any concern that the propensity to select out of sample during the course of a program might

[22] All specifications include a course-level fixed effect (e.g. second-year or 2000-level courses), to disentangle the effect of course difficulty from the number of years enrolled. The correlation between course level and years enrolled is 0.65.

be different between domestic and foreign students. The results here suggest that among domestic students there is indeed disproportionate attrition of cold-sensitive students, as we would expect, but little evidence that the same applies to their foreign counterparts.

To explore adaptation over time, in column 3 we look at all exams taken, but include an interaction term between temperature and number of years enrolled. The exercise is repeated in column 4 where we restrict attention to that subset of students who ultimately graduate. The temperature $\times$ years enrolled coefficients are small and statistically insignificant, indicating that as domestic students spend more time at the university their sensitivity to cold does not change. The large and statistically significant coefficient on the triple interaction term – how foreign student's sensitivity changes over time – indicates as these students spend more time in Ottawa they become substantially less sensitive to cold. Among both the entire sample and the students who ultimately graduate, the differential between domestic and foreign students is eroded such that it is nearly eliminated after roughly 3 years from their first exam season. This is consistent with the notion of habituation or psychological cold tolerance "... depending largely on the individual's familiarity with cold" (Enander, 1984).

## 8. Robustness

In Table 11 we challenge the robustness of our main results by re-estimating our preferred specification using alternative temperature measures (corresponding to column 6 in Table 2, which is reproduced in column 1 here).

**Alternative temperature metrics** The treatment variable of interest throughout the study has been same-day mean temperature. This is calculated as the average of the daily maximum temperature and the minimum temperature. In columns 2 through 5 we replace this measure with alternatives. In column 2 the 24 hour (equally-weighted) daily average temperature, in column 3 the daily minimum temperature, in column 4 exam time temperature, and in column 5 temperature measured at the next closest weather station (Ottawa International Airport, 14 km from the centre of campus). In each case, the qualitative result sustains - cold outdoor temperature causes a decrement in indoor performance. For comparability between the columns we have also included the mean and standard deviation of the temperature measure applied in each.

**Outliers** To explore the possibility that the estimated effects are driven by a small number of outliers, we winsorize the treatment variable in column 6. Specifically, we assign the coldest 10% of observations the 10th percentile temperature value and the

10% of warmest observations the 90th percentile value. The results of this exercise are largely the same as our preferred, discouraging the view that our effect is driven by a small number of extreme observations.

**Precipitation** Throughout the analysis we have been careful to control for the role that precipitation might play, both in its own right and in interaction with temperature. As an additional exercise we reestimate our main specification on the 288,717 exams taken on those days when there was no precipitation ('dry days'). The results are reported in column 7 of Table 11. The sign and significance of the coefficient estimate are sustained, while the coefficient is somewhat larger in value. That we observed the effect even on days absent precipitation provides reassurance that our main specification does a good job of isolating temperature effects from the possible confounding effects of precipitation.

'**No controls' specification** All of our specifications have included basic controls, for example same-day precipitation. For transparency we report a skeletal specification in which the only regressor is temperature in column 8. Our results sustain.

**Placebo** As a further test for flaws in our study design that could generate spurious associations between our temperature and performance measures we report here the results of a placebo exercise.

For each student there is vector of exam dates and a vector of associated exam temperatures. To generate placebo temperatures, we separate the two vectors, randomize the order of the exam temperature vector and reattach them. This reassigns temperature treatments randomly without replacement, within-student. Once reattached, recognizing the likely serial correlation within a particular December, we drop any exams for which the randomization assigned a placebo temperature from the same exam period (this necessarily drops any student who writes exams only in a single exam period). The preferred specification is re-estimated with these falsely-assigned treatment values, generating a single coefficient value and associated t-statistic. We repeat this 1,000 times, generating 1,000 temperature coefficient values and 1,000 t statistics. The distributions of these are plotted in Figure 6. It can be seen that the values derived from the main analysis for both coefficient (0.809) and t statistic (10.408) lie far to the right of any of the placebo-generated values.

**Alternative standard errors** In Table 12 we report the results of using alternative standard errors for our main analysis. Our main analysis reported standard errors clustered at the student level, corresponding with the panel setting of our data. It is likely that observations within student are correlated (even after accounting for individual fixed effects). Because of this we also apply Huber-White heteroskedasticity robust standard errors. In the second column we provide standard errors that are unclustered and find no meaningful changes in their size. In the third column, we cluster by student cohort, clustering at what could be considered treatment level (for example cold in first year could be different than cold in second year, and cohort determines this inter-year pattern). The challenge here is the low number of cohorts available, forcing us to bootstrap. While the standard errors as measured in this manner are around three times larger, our effect size is still significant at a level well beyond 1%. In column 4 we define treatment levels by exam temperature ventiles and cluster at that level, again with no impact on our conclusions.

## 9. Conclusions

It is obvious that extreme weather can make those working outdoors less productive. However, any link from outdoor temperature to the quantity and quality of work done in indoor, climate-protected environments is potentially crucial in understanding the climate-economy connection, especially in sectors that are not obviously climate-sensitive, such as agriculture.

While a small number of studies have cast light on this question in the case of extreme heat (generally temperatures over about 30°C) we look to the other end of the temperature distribution, finding substantial and apparently robust effects of low outdoor temperature on internal cognitive performance in our setting. That (a) the effect persists even though the students are protected by close-to-perfect climate control, (b) the effect size appears insensitive to the "amount" of exposure that an individual student experiences directly and, (c) sensitivity amongst those new to such temperatures diminishes with repeated exposure, all fit with existing evidence from psychology and biology that the main mechanism or mechanisms at play may be psychological rather than physiological in nature. Our results are consistent with psychological habituation as adaptation, which although less than complete, is able to nullify the difference in sensitivity between locals and those arriving from warmer climates in the space of around three annual cycles.

The analysis points to a previously unaccounted for benefit of climate change in historically cold places projected in future to experience less cold days. At the same time an unaccounted for cost of climate change in places projected to experience more cold days - in particular those impacted by the weakening of the polar vortex. Additional distribution effects come from secondary results, for example we that men are more sensitive to cold temperatures than women. And the affluent are better insulated from the cold.

Our setting provided the opportunity to conduct a detailed analysis of the scope for adaptation at various loci. While in most cases we found evidence consistent with the protective benefits of adaptation, in no case was the protection complete.

While the performance of university students taking exams is an important social outcome in its own right, the quantitative impacts of the insights of the effect identified depend upon the extent of external validity. If similar decrements in performance were to occur in the workplace, especially in those settings involving high-value, mentally taxing work, the implied economic burden of cold days (alternatively, the *benefits* associated with any reduction in the frequency of cold days) would be large. Investigating the generality of any effects identified here could be a fruitful area of future research.

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## Tables and Figures

Table 1: Summary Statistics

| | All | Female | Male | Domestic | Foreign |
|---|---|---|---|---|---|
| Course Grade | 71.98 | 72.87 | 70.62 | 72.27 | 67.93 |
| | (10.31) | (9.82) | (11.02) | (10.16) | (12.22) |
| Temperature (°C) | -5.13 | -5.21 | -5.01 | -5.22 | -3.96 |
| | (5.68) | (5.68) | (5.67) | (5.69) | (5.59) |
| Precipitation (mm) | 2.12 | 2.13 | 2.1 | 2.13 | 1.99 |
| | (4.12) | (4.14) | (4.09) | (4.14) | (3.77) |
| Snow on Ground (cm) | 2.46 | 2.46 | 2.46 | 2.48 | 2.17 |
| | (2.74) | (2.73) | (2.75) | (2.76) | (2.47) |
| Foreign | 7.43 | 5.79 | 9.89 | - | 100.00 |
| Female | 60.00 | 100.00 | - | 61.06 | 46.77 |
| Exams | 638,238 | 384,716 | 253,522 | 595,794 | 42,444 |
| Students | 66,715 | 40,140 | 26,575 | 61,814 | 4,901 |

Notes: Within-student standard deviations presented. Foreign and female statistics refer to the proportion of exams written by foreign and female students, respectively. Foreign students are classified by immigration status or payment of international student fees.

Table 2: Temperature and Performance (Linear)

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score Preferred |
|---|---|---|---|---|---|---|
| Temperature (°C) | 0.833*** | 0.789*** | 0.699*** | 0.750*** | 0.742*** | 0.809*** |
| | (0.043) | (0.043) | (0.045) | (0.047) | (0.047) | (0.078) |
| Precipitation | Y | Y | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y | Y | Y |
| Day of Week FE | | Y | Y | Y | Y | Y |
| Date in Month | | | Y | Y | Y | Y |
| Relative Humidity | | | | Y | Y | Y |
| Snow on Ground | | | | | Y | Y |
| Windchill | | | | | | Y |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 3: Temperature and Performance (Non-linear)

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score Preferred |
|---|---|---|---|---|---|---|
| -15°$C$ | 7.670*** | 4.621*** | 4.376*** | 4.091*** | 4.300*** | 3.782*** |
| | (1.091) | (1.119) | (1.120) | (1.123) | (1.124) | (1.161) |
| -12.5°$C$ | -2.887** | -6.465*** | -6.760*** | -6.729*** | -6.651*** | -7.374*** |
| | (1.354) | (1.385) | (1.387) | (1.388) | (1.387) | (1.452) |
| -10°$C$ | 14.569*** | 10.651*** | 9.296*** | 8.853*** | 7.650*** | 6.756*** |
| | (1.108) | (1.126) | (1.170) | (1.175) | (1.179) | (1.296) |
| -7.5°$C$ | 11.446*** | 7.539*** | 6.755*** | 6.377*** | 3.870*** | 2.479* |
| | (1.140) | (1.189) | (1.205) | (1.210) | (1.227) | (1.497) |
| -5°$C$ | 15.080*** | 11.653*** | 11.101*** | 11.522*** | 10.807*** | 9.362*** |
| | (1.160) | (1.167) | (1.175) | (1.185) | (1.186) | (1.472) |
| -2.5°$C$ | 16.067*** | 13.886*** | 13.020*** | 13.511*** | 13.358*** | 11.565*** |
| | (1.080) | (1.088) | (1.105) | (1.118) | (1.118) | (1.557) |
| 0°$C$ | 16.788*** | 14.983*** | 13.423*** | 13.875*** | 14.170*** | 12.213*** |
| | (1.214) | (1.248) | (1.297) | (1.309) | (1.308) | (1.771) |
| 2.5°$C$ | 35.063*** | 33.134*** | 30.633*** | 30.903*** | 32.970*** | 30.877*** |
| | (1.637) | (1.665) | (1.760) | (1.763) | (1.772) | (2.184) |
| Precipitation | Y | Y | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y | Y | Y |
| Day of Week FE | | Y | Y | Y | Y | Y |
| Date in Month | | | Y | Y | Y | Y |
| Relative Humidity | | | | Y | Y | Y |
| Snow on Ground | | | | | Y | Y |
| Windchill | | | | | | Y |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variables are exam day average temperature bins 2.5 degrees Celsius wide. The reference bin is exam days with temperatures below -15°C. Each bin is separately interacted with precipitation. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 4: Heterogeneity

| | (1) Sex | (2) 80 Admission Average | (3) Foreign |
|---|---|---|---|
| Temperature °C | 0.927*** | 0.940*** | 0.778*** |
| | (0.091) | (0.084) | (0.078) |
| Female=1 × Temperature °C | -0.192*** | | |
| | (0.073) | | |
| 80 Admission Average=1 × Temperature °C | | -0.311*** | |
| | | (0.072) | |
| Foreign=1 × Temperature °C | | | 0.486*** |
| | | | (0.162) |
| Precipitation | Y | Y | Y |
| Temp × Precip | Y | Y | Y |
| Day of Week FE | Y | Y | Y |
| Date in Month | Y | Y | Y |
| Relative Humidity | Y | Y | Y |
| Snow on Ground | Y | Y | Y |
| Windchill | Y | Y | Y |
| Exams | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. The second independent variable of interest is the interaction between exam day temperature and a subsample identifier. High admission students have an 'A' admission average. Foreign students are classified by immigration status or international fees. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 5: Semester Temperature and Performance

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score |
|---|---|---|---|---|
| Temperature °C | 0.809*** | 0.798*** | 0.787*** | 0.791*** |
| | (0.078) | (0.078) | (0.078) | (0.078) |
| Total HDD Last 30 Days | | 0.034*** | | |
| | | (0.011) | | |
| Total HDD Last 60 Days | | | 0.076*** | |
| | | | (0.009) | |
| Total HDD Last 90 Days | | | | 0.057*** |
| | | | | (0.012) |
| Precipitation | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y |
| Exams | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day heating degree days - the number of degrees below 18°C. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 6: Climate Control

| | (1) New Building Interaction 1 | (2) New Building Interaction 2 | (3) Exclude Leaky Rooms |
|---|---|---|---|
| Temperature (°C) | 0.837*** | 0.795*** | 0.628*** |
| | (0.081) | (0.081) | (0.086) |
| New Building=1 | -5.825*** | -5.661*** | -3.517*** |
| | (0.507) | (0.507) | (0.527) |
| New Building=1 × Temperature (°C) | -0.113* | -0.136** | -0.031 |
| | (0.061) | (0.061) | (0.063) |
| Course Level FE | | Y | Y |
| Precipitation | Y | Y | Y |
| Temp × Precip | Y | Y | Y |
| Year FE | Y | Y | Y |
| Day of Week FE | Y | Y | Y |
| Date in Month | Y | Y | Y |
| Relative Humidity | Y | Y | Y |
| Snow on Ground | Y | Y | Y |
| Windchill | Y | Y | Y |
| Exams | 638238 | 638238 | 587030 |
| Students | 66715 | 66715 | 66615 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. The secondary variable of interest is the interaction between a new building (completed after or during 2000 C.E.). Leaky rooms have internal temperature readings outside a ± 1°C tolerance band. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 7: Travel to Work

| | (1) All | (2) Movers | (3) ≤10km Non-Movers |
|---|---|---|---|
| Temperature (°C) | 0.719*** | 0.782*** | 0.866*** |
| | (0.081) | (0.236) | (0.288) |
| Distance (km) | -0.003 | -0.002 | |
| | (0.004) | (0.004) | |
| Temperature (°C) × Distance (km) | 0.000 | 0.000 | -0.025 |
| | (0.000) | (0.000) | (0.036) |
| Precipitation (mm) | -0.437*** | -0.438*** | -0.980*** |
| | (0.060) | (0.170) | (0.297) |
| Temperature (°C) × Precipitation (mm) | -0.103*** | -0.095*** | -0.121*** |
| | (0.010) | (0.032) | (0.025) |
| Distance (km) × Precipitation (mm) | -0.000 | -0.000 | 0.084* |
| | (0.000) | (0.000) | (0.044) |
| Snow on Ground (cm) | -0.513*** | -0.631*** | -0.161 |
| | (0.054) | (0.161) | (0.232) |
| Distance (km) × Snow on Ground (cm) | 0.000 | -0.000 | -0.043 |
| | (0.000) | (0.000) | (0.032) |
| Day of Week FE | Y | Y | Y |
| Date in Month | Y | Y | Y |
| Relative Humidity | Y | Y | Y |
| Windchill | Y | Y | Y |
| Exams | 598407 | 81347 | 107380 |
| Students | 62596 | 8530 | 11514 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. The second independent variable of interest is the interaction between temperature and distance to student address (measured in km). Movers are students whose term address is different than their enrolment address. Students whose addresses are never more than 50km from campus. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 8: Family Affluence Proxy

| | (1)<br>All | (2)<br>Domestic |
|---|---|---|
| Temperature (°C) | 0.991*** | 0.939*** |
| | (0.123) | (0.127) |
| Temperature (°C) × Avg. Income | -0.037** | -0.038** |
| | (0.018) | (0.019) |
| Precipitation | Y | Y |
| Temp × Precip | Y | Y |
| Day of Week FE | Y | Y |
| Date in Month | Y | Y |
| Relative Humidity | Y | Y |
| Snow on Ground | Y | Y |
| Windchill | Y | Y |
| Exams | 627352 | 588005 |
| Students | 65404 | 60962 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius.The second independent variable of interest is the interaction between temperature and average income of student address at enrolment (from 2016 Census data). Average income measured in 10,000's CAD. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 9: Heterogeneity Among Arrivees

| | (1)<br>Method 1<br>Probably Hot | (2)<br>Method 1<br>Other | (3)<br>Method 2<br>Probably Hot | (4)<br>Method 2<br>Other |
|---|---|---|---|---|
| Temperature (°C) | 4.591*** | 1.226*** | 2.992*** | 1.495*** |
| | (1.048) | (0.401) | (0.796) | (0.425) |
| Precipitation | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y |
| Exams | 6308 | 36136 | 9907 | 32537 |
| Students | 985 | 3916 | 1275 | 3626 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. The first column estimates the preferred specification on international students who take all of their courses in French. The second column estimates our preferred specification on international students who took none (N=3,085), or some fraction of their studies (N=981) in French. In the third and fourth column we relax our definition of probably hot country students to those who take all of their first year courses in French. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 10: Adaptation of Arrivees Over Time

| | (1) All (Year 1 Exams) | (2) Graduates (Year 1 Exams) | (3) All | (4) Graduates |
|---|---|---|---|---|
| Temperature (°C) | 1.124*** | 0.498*** | 0.695*** | 0.358*** |
| | (0.129) | (0.163) | (0.087) | (0.098) |
| Foreign=1 × Temperature (°C) | 0.855*** | 1.300*** | 0.866*** | 1.100*** |
| | (0.318) | (0.452) | (0.252) | (0.326) |
| Temperature (°C) × Years Enrolled | | | 0.022 | 0.035 |
| | | | (0.031) | (0.033) |
| Foreign=1 × Temperature (°C) × Years Enrolled | | | -0.237* | -0.394** |
| | | | (0.139) | (0.159) |
| Course Level FE | Y | Y | Y | Y |
| Precipitation | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y |
| Exams | 265804 | 136319 | 638238 | 426583 |
| Students | 66447 | 33228 | 66715 | 33322 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. All specifications include course-level fixed effects (e.g. 2000 level courses). Years enrolled begins at 0 for the first winter of exams, and typically ends at 3 years. In columns 1 and 2, we estimate only on the first year's course results and do not include year fixed effects. Columns 3 and 4 include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Table 11: Robustness

| | (1) Mean Temp (Preferred) | (2) 24 Hour Average | (3) Min Temp | (4) Exam Temp | (5) Next Station | (6) Winsorized at 10% | (7) Dry Days | (8) No Controls |
|---|---|---|---|---|---|---|---|---|
| Temp. Measure | 0.809*** | 0.771*** | 0.386*** | 0.603*** | 0.532*** | 0.724*** | 0.963*** | 1.526*** |
| | (0.078) | (0.080) | (0.064) | (0.095) | (0.075) | (0.094) | (0.128) | (0.035) |
| Precipitation | Y | Y | Y | Y | Y | Y | | |
| Temp × Precip | Y | Y | Y | Y | Y | Y | | |
| Day of Week FE | Y | Y | Y | Y | Y | Y | Y | |
| Date in Month | Y | Y | Y | Y | Y | Y | Y | |
| Relative Humidity | Y | Y | Y | Y | Y | Y | Y | |
| Snow on Ground | Y | Y | Y | Y | Y | Y | Y | |
| Windchill | Y | Y | Y | Y | Y | Y | Y | |
| Mean of Measure | -5.14 | -4.76 | -8.68 | -4.16 | -5.3 | -5.12 | -6.64 | -5.14 |
| SD of Measure | 6.61 | 6.45 | 7.51 | 6.52 | 6.75 | 5.52 | 6.66 | 6.61 |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 | 288717 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 | 64016 | 66715 |

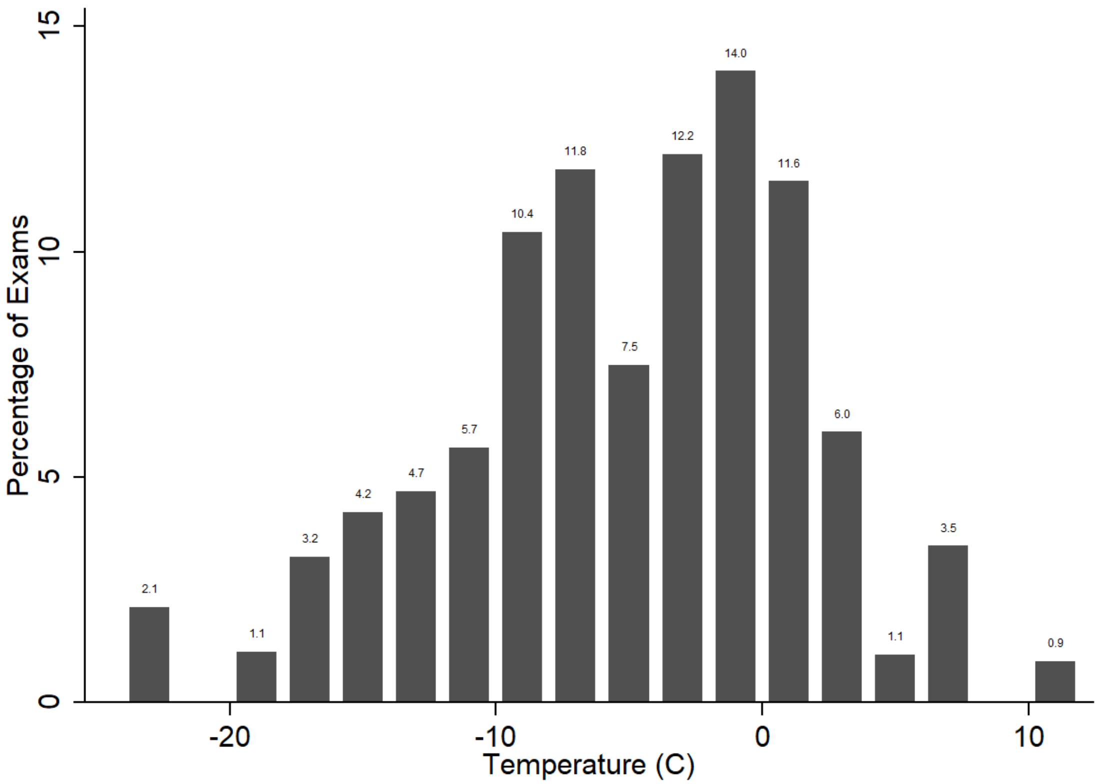
The dependent variable is hundredths of a standard deviation in final exam grade. Each column title denotes the primary independent variable. The first column is average exam day temperature in degrees Celsius, calculated as the average of daily maximum and minimum. The second column is the 24 hour equally weighted average temperature. The third column uses daily minimum temperature. The fourth column uses the average hourly temperature during the 3 hour window of the exam. The fifth column uses daily average temperature from the next-closest weather station (an international airport approximately 14km away). The sixth uses temperatures winsorized at the 10% and 90% level. The seventh column estimates the preferred specification only on days without precipitation. The eighth column simply regresses performance and temperature. Other than 'no controls', all specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table 12: Alternative Standard Errors

| | (1) Preferred Student | (2) Unclustered | (3) Cohort (Bootstrap) | (4) Exam Ventiles |
|---|---|---|---|---|
| Temperature (°C) | 0.809*** | 0.809*** | 0.809*** | 0.809*** |
| | (0.078) | (0.078) | (0.252) | (0.225) |
| Precipitation | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y |
| Exams | 638238 | 638238 | 638238 | 638238 |
| Clusters | 66715 | | 9 | 20 |

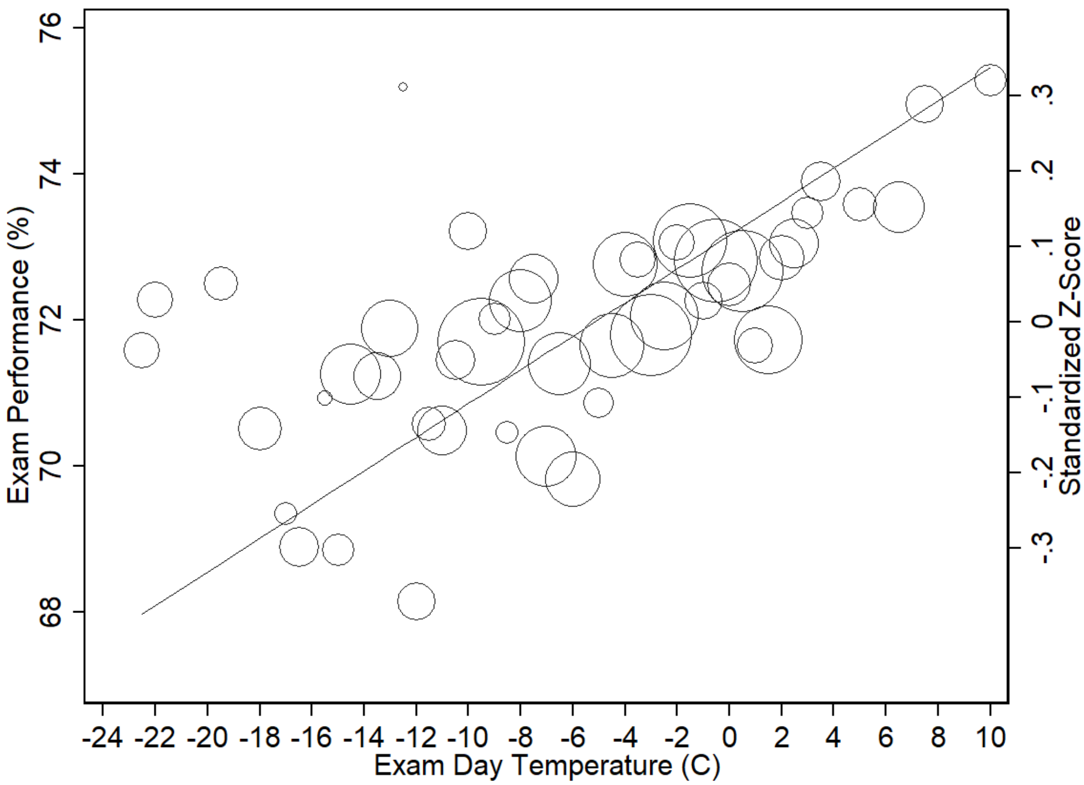
The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. (1) errors clustered at the student level (2) unclustered errors (3) bootstrapped errors clustered by cohort (4) ventiles of average exam temperatures. All specifications include year fixed effects. Within-student fixed effects model. The sample comprises all exams written in December from 2007-2015. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$.)

Figure 1: Distribution of Temperature Treatments



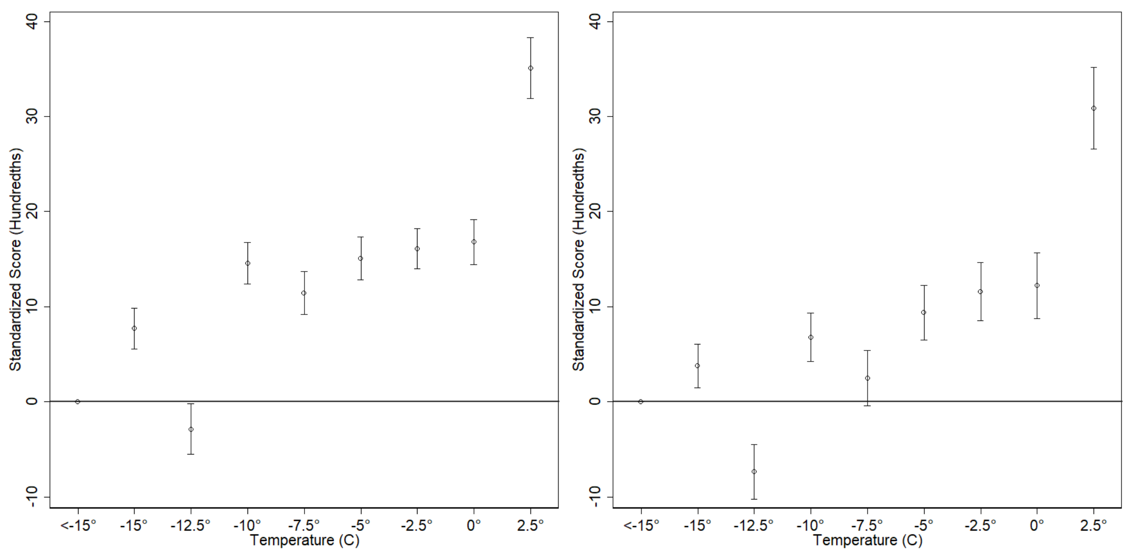

In this figure, we plot the percentage of exams written on days with average temperatures divided into 2 degree Celsius bins. Each exam, rather than each exam day, represents a single observation.

Figure 2: Temperature and Performance (Only Year Controls)



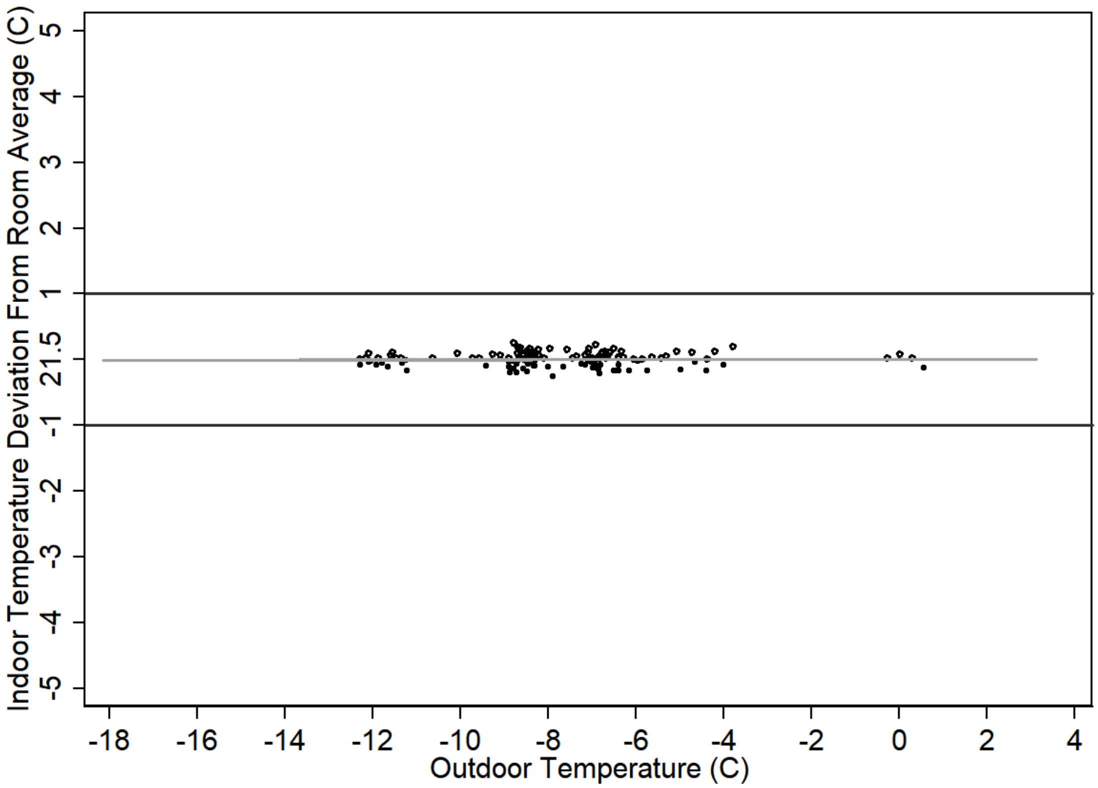

In this figure, we plot the imputed residual exam grade (after accounting for year fixed effects) by exam day temperature. Temperature is rounded to the nearest 0.5°C. Markers are sized proportional to number of observations they represent.

Figure 3: Temperature and Performance (Non-Linear)



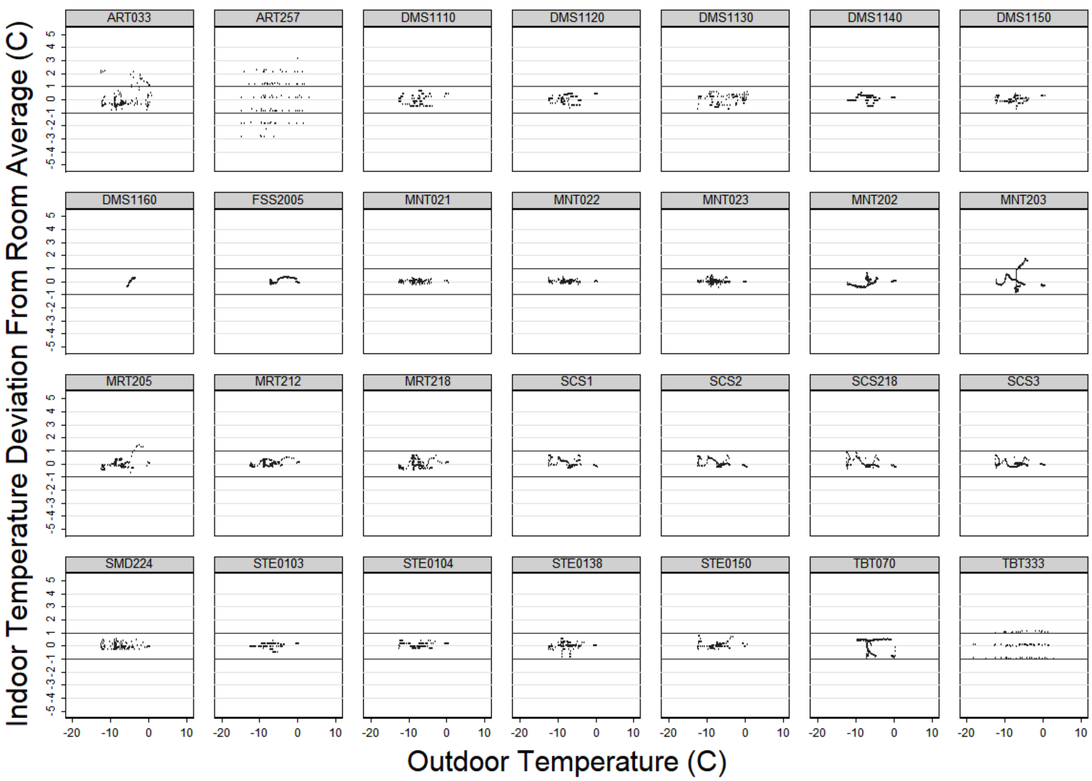

In this figure, we present the estimated coefficients by "binning" daily temperatures into 2.5°C intervals. The reference category is exams written with daily temperatures below -15°C. The dependent variable is exam score standard deviations in hundredths. The left panel corresponds to a parsimonious specification with student and year fixed effects, precipitation, and its interaction with each temperature bin. The right panel corresponds to our preferred specification with additional controls. Whiskers indicate the 95% confidence level.

Figure 4: Indoor and Outdoor Temperatures (MNT021)



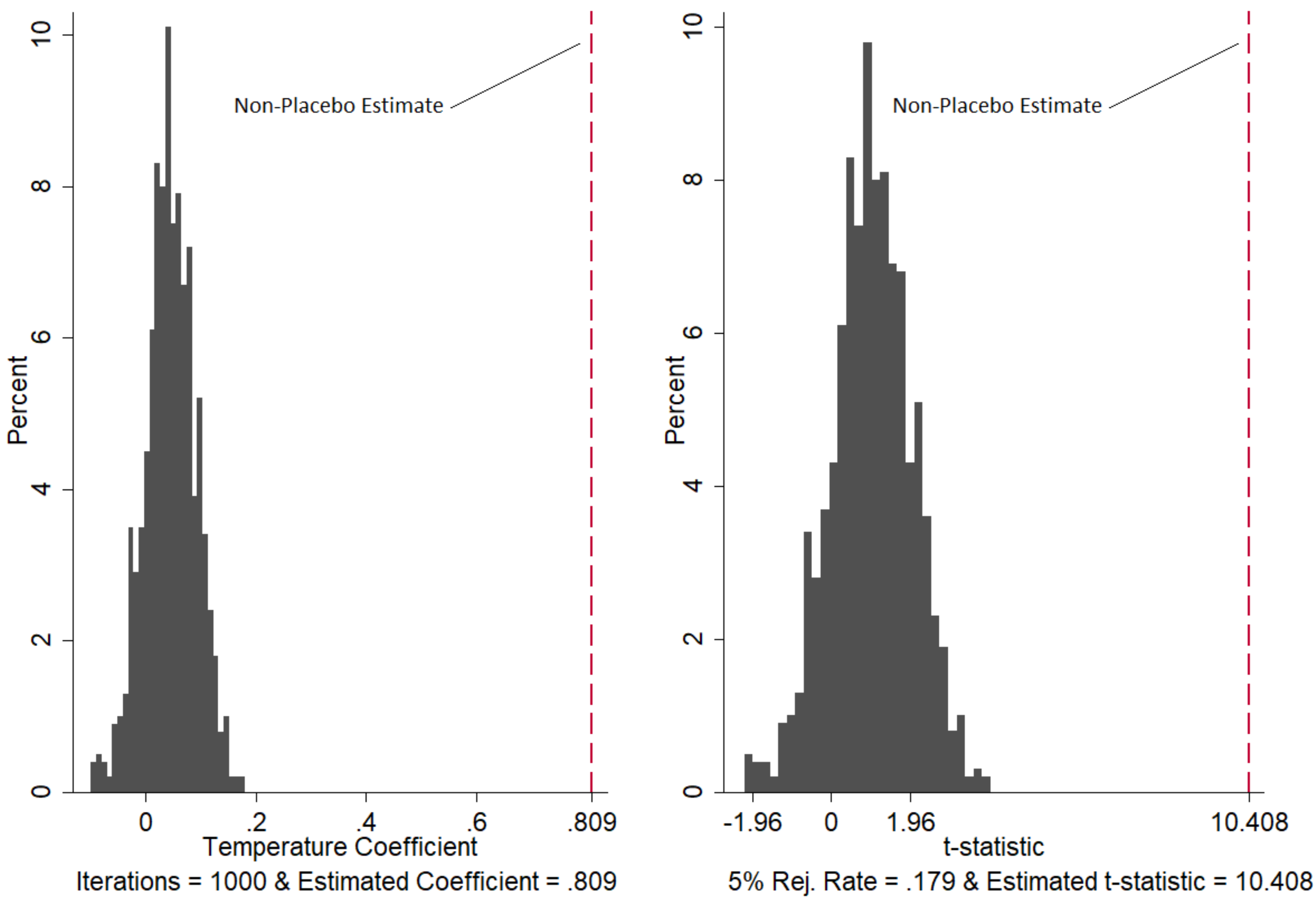

In this figure, we plot the outdoor temperatures realized during 2018 December exams and the internal temperature variations from room average in the largest exam room by contribution to sample. We fit a regression line with slope coefficient of 0.0003 and an associated t-statistic of 0.10. Reference lines are provided at 1°C (above) and -1°C (below) room average.

Figure 5: Indoor and Outdoor Temperatures (Room by Room)




In this figure, we plot the outdoor temperatures realized during 2018 December exams and the internal temperature variations from room average by exam room. Reference lines are provided at 1°C (above) and -1°C (below) room average.

Figure 6: Placebo




In this figure, we present histograms of the estimated temperature coefficients and associated t-statistics for a placebo exam day temperature. Placebo temperatures are randomized within-student and without replacement. If an exam was assigned a placebo temperature from the same exam season, that observation was dropped. The preferred specification in Table 2 was run 1,000 times. A reference line corresponding to our preferred specification, on the correct exam day temperature, is provided in each panel.

## Appendices

Table A1: Temperature and Performance (Linear)

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score | (7) Z-Score | (8) Z-Score Preferred |
|---|---|---|---|---|---|---|---|---|
| Temperature (°C) | 0.609*** | 0.688*** | 0.833*** | 0.789*** | 0.699*** | 0.750*** | 0.742*** | 0.809*** |
| | (0.040) | (0.042) | (0.043) | (0.043) | (0.045) | (0.047) | (0.047) | (0.078) |
| Precipitation | | -0.387*** | -0.712*** | -0.451*** | -0.425*** | -0.355*** | -0.419*** | -0.425*** |
| | | (0.046) | (0.050) | (0.052) | (0.052) | (0.055) | (0.055) | (0.055) |
| Temp × Precip | | | -0.128*** | -0.117*** | -0.107*** | -0.112*** | -0.105*** | -0.104*** |
| | | | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Date in Month | | | | | -0.353*** | -0.315*** | -0.015 | -0.013 |
| | | | | | (0.053) | (0.054) | (0.062) | (0.062) |
| Relative Humidity | | | | | | -0.077*** | -0.025 | -0.019 |
| | | | | | | (0.019) | (0.019) | (0.020) |
| Snow on Ground | | | | | | | -0.500*** | -0.503*** |
| | | | | | | | (0.051) | (0.051) |
| Windchill | | | | | | | | -0.037 |
| | | | | | | | | (0.034) |
| Day of Week FE | | | | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A2: Temperature and Performance (Deciles)

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score Preferred |
|---|---|---|---|---|---|---|
| -14.7°$C$ | 6.805*** | 4.484*** | 4.277*** | 3.796*** | 2.916*** | 1.733 |
| | (1.030) | (1.051) | (1.052) | (1.057) | (1.061) | (1.117) |
| -10.6°$C$ | 8.666*** | 3.514*** | 1.960* | 1.376 | -1.192 | -3.243** |
| | (1.113) | (1.148) | (1.168) | (1.171) | (1.206) | (1.363) |
| -8.3°$C$ | 18.341*** | 14.276*** | 12.494*** | 11.755*** | 9.297*** | 6.572*** |
| | (1.075) | (1.102) | (1.131) | (1.138) | (1.170) | (1.431) |
| -6.5°$C$ | 8.474*** | 5.319*** | 5.282*** | 5.113*** | 3.070** | -0.023 |
| | (1.211) | (1.234) | (1.234) | (1.234) | (1.256) | (1.585) |
| -4.1°$C$ | 19.629*** | 12.205*** | 11.748*** | 12.589*** | 12.015*** | 8.621*** |
| | (1.317) | (1.355) | (1.358) | (1.367) | (1.368) | (1.715) |
| -2.7°$C$ | 11.557*** | 7.405*** | 5.992*** | 6.711*** | 5.041*** | 1.005 |
| | (1.127) | (1.137) | (1.155) | (1.163) | (1.177) | (1.702) |
| -.7°$C$ | 17.268*** | 14.313*** | 13.270*** | 14.719*** | 13.635*** | 9.348*** |
| | (1.184) | (1.199) | (1.208) | (1.240) | (1.244) | (1.802) |
| .3°$C$ | 15.850*** | 14.862*** | 12.868*** | 13.693*** | 12.730*** | 8.327*** |
| | (1.208) | (1.245) | (1.275) | (1.287) | (1.291) | (1.862) |
| 2.2°$C$ | 27.861*** | 23.528*** | 20.719*** | 21.947*** | 21.914*** | 17.239*** |
| | (1.534) | (1.574) | (1.627) | (1.649) | (1.649) | (2.182) |
| Precipitation | Y | Y | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y | Y | Y |
| Day of Week FE | | Y | Y | Y | Y | Y |
| Date in Month | | | Y | Y | Y | Y |
| Relative Humidity | | | | Y | Y | Y |
| Snow on Ground | | | | | Y | Y |
| Windchill | | | | | | Y |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variables are exam day average temperature deciles. The reference bin is exam days with temperatures below -14.7°C. Each bin is separately interacted with precipitation. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A3: Semester Temperature and Performance

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score | (7) Z-Score |
|---|---|---|---|---|---|---|---|
| Temperature (°C) | 0.809*** | 0.796*** | 0.964*** | 0.839*** | 0.798*** | 0.786*** | 0.803*** |
| | (0.078) | (0.091) | (0.083) | (0.080) | (0.078) | (0.078) | (0.078) |
| Avg. Temp. Last 1 Days | | 0.017 | | | | | |
| | | (0.058) | | | | | |
| Avg. Temp. Last 3 Days | | | -0.307*** | | | | |
| | | | (0.065) | | | | |
| Avg. Temp. Last 5 Days | | | | -0.108 | | | |
| | | | | (0.080) | | | |
| Avg. Temp. Last 30 Days | | | | | -1.028*** | | |
| | | | | | (0.318) | | |
| Avg. Temp. Last 60 Days | | | | | | -4.580*** | |
| | | | | | | (0.559) | |
| Avg. Temp. Last 90 Days | | | | | | | -4.395*** |
| | | | | | | | (1.152) |
| Precipitation | Y | Y | Y | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y | Y | Y | Y |
| Exams | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 | 638238 |
| Students | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 | 66715 |

The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day temperature. The secondary independent variable is average temperature leading up to exam day. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A4: Travel to Work (Subsamples)

| | (1)<br>≤2km | (2)<br>≤5km | (3)<br>≤10km | (4)<br>≤20km |
|---|---|---|---|---|
| Temperature (°C) | 0.919* | 0.725** | 0.770*** | 0.834*** |
| | (0.532) | (0.359) | (0.214) | (0.174) |
| Precipitation | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y |
| Day of Week FE | Y | Y | Y | Y |
| Date in Month | Y | Y | Y | Y |
| Relative Humidity | Y | Y | Y | Y |
| Snow on Ground | Y | Y | Y | Y |
| Windchill | Y | Y | Y | Y |
| Exams | 14182 | 31379 | 88217 | 113229 |
| Students | 1966 | 3699 | 9771 | 11618 |

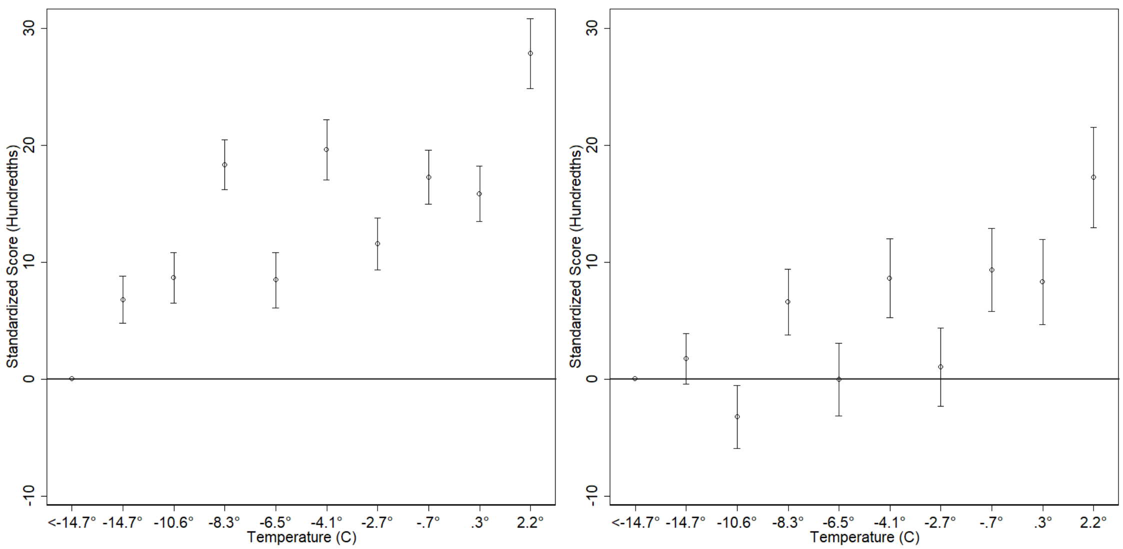
The dependent variable is hundredths of a standard deviation in final exam grade. The primary independent variable is exam day average temperature in degrees Celsius. Each column header indicates the outer radius of successively distant donut-shaped regions. The second column estimates our effect for addresses 2.0 km to 5.0 km from campus. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Table A5: Temperature and Performance, Alternative Standardization

| | (1) Z-Score | (2) Z-Score | (3) Z-Score | (4) Z-Score | (5) Z-Score | (6) Z-Score Preferred |
|---|---|---|---|---|---|---|
| Temperature (C) | 0.730*** | 0.689*** | 0.524*** | 0.605*** | 0.604*** | 1.039*** |
| | (0.043) | (0.044) | (0.046) | (0.047) | (0.047) | (0.079) |
| Precipitation | Y | Y | Y | Y | Y | Y |
| Temp × Precip | Y | Y | Y | Y | Y | Y |
| Day of Week FE | | Y | Y | Y | Y | Y |
| Date in Month | | | Y | Y | Y | Y |
| Relative Humidity | | | | Y | Y | Y |
| Snow on Ground | | | | | Y | Y |
| Windchill | | | | | | Y |
| Exams | 638185 | 638185 | 638185 | 638185 | 638185 | 638185 |
| Students | 66713 | 66713 | 66713 | 66713 | 66713 | 66713 |

The dependent variable is hundredths of a standard deviation in final exam grade, standardized by year and course. The primary independent variable is exam day average temperature in degrees Celsius. All specifications include year fixed effects. Within-student fixed effects model. Heteroskedasticity robust standard errors are in parentheses, clustered at the student level. The sample comprises all exams written in December from 2007-2015. (*** p<0.01, ** p<0.05, * p<0.1.)

Figure A1: Temperature and Performance (Deciles)




In this figure, we present the estimated coefficients for indicator variables created by assigning daily temperatures into decile intervals. The reference category is exams written in the 10% coldest daily average temperatures. The dependent variable is exam score standard deviations in hundredths. The left panel corresponds to a parsimonious specification with student and year fixed effects, precipitation, and its interaction with each temperature bin. The right panel corresponds to our preferred specification with additional controls. Whiskers indicate the 95% confidence level.

Figure A2: Precipitation

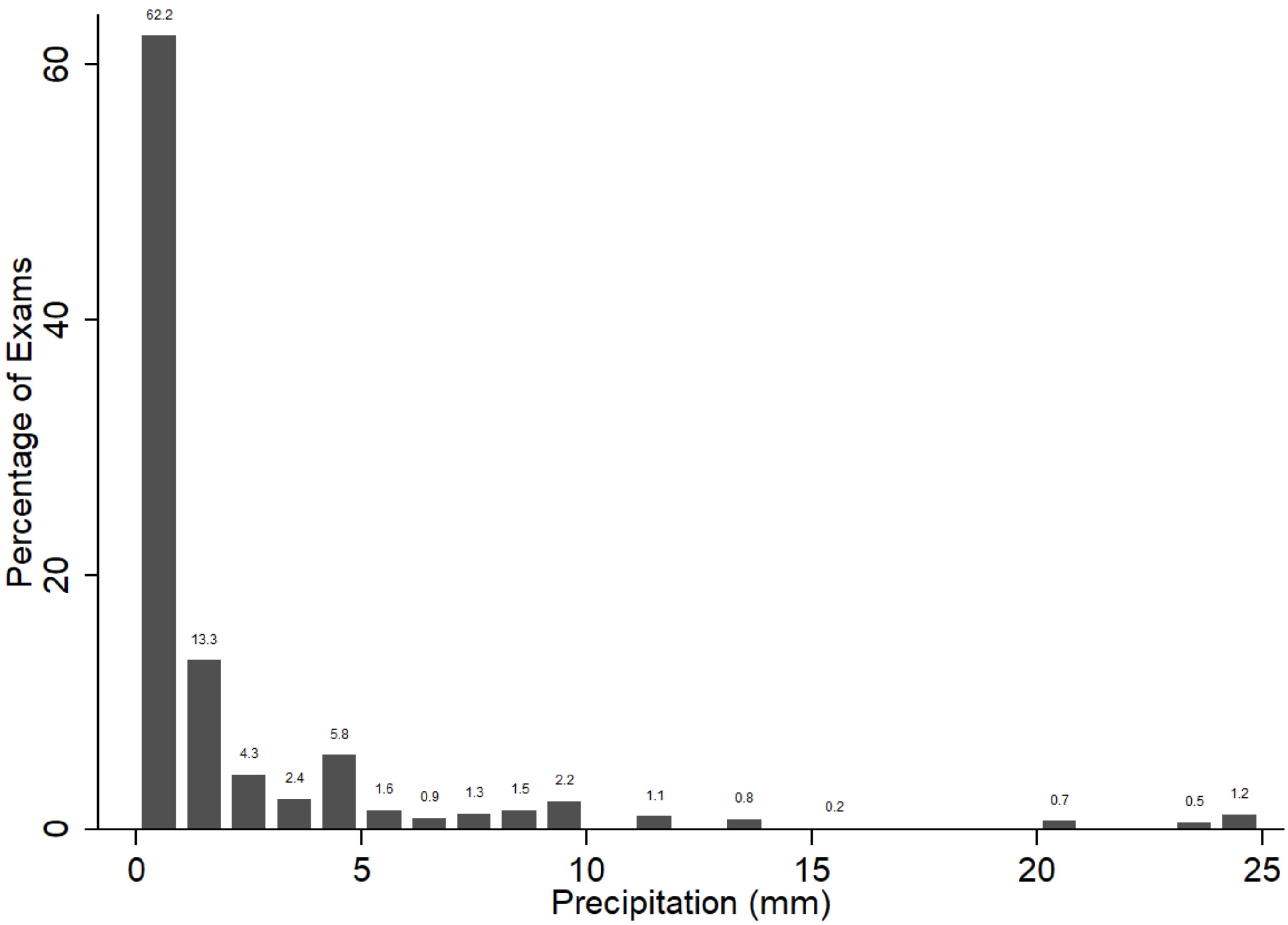


Figure A3: Snow on Ground

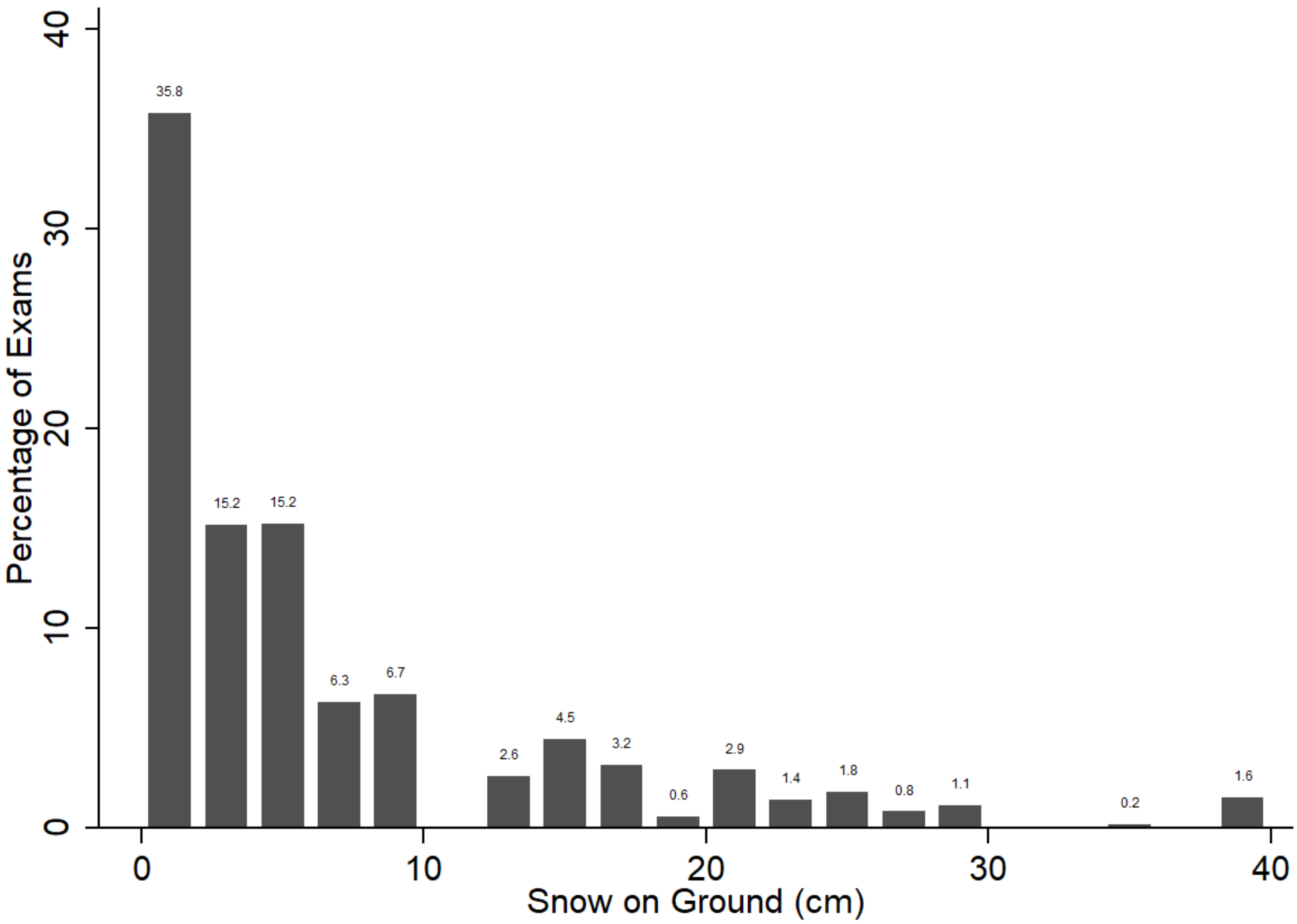


Figure A4: Distance to Student Address

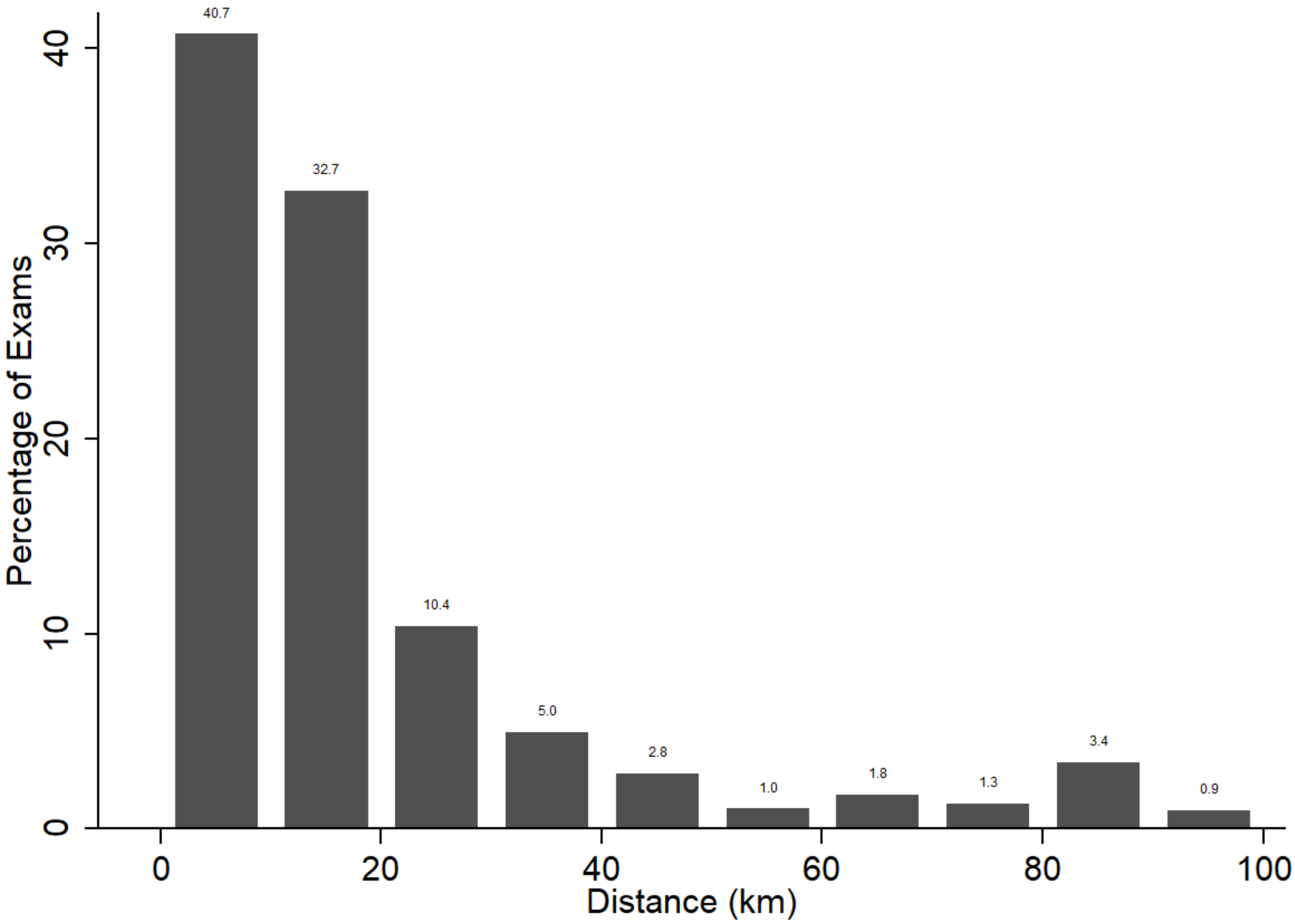


Figure A5: Student Application Address Average Income